Research on the Hierarchical Structure of User Feature Factors Affecting the Accurate Recommendation of Digital Educational Resources

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***Abstract*—In order to analyze the user characteristic factors that affect the accurate recommendation of digital educational resources, optimize the user model and improve the accuracy of resource recommendation. In this paper, the interpretive structure Model (ISM) technology is used to clarify the logical relations among 13 key feature factors and establish the interpretive structure hierarchy model. Then the MICMAC model is used to analyze the dependence and driving force of each characteristic factor to determine its influence degree. The results show that user resource needs, resource preference and learning style are the direct factors affecting digital educational resource recommendation service. Individual attribute, learning motivation, social attribute, interactive preference, learning emotion and learning attitude are the core factors that affect the recommendation of digital educational resources. Information literacy, knowledge level, cognitive structure and learning input are the source factors that affect the recommendation of digital educational resources. Combining ISM analysis and MICMAC classification, the stability and driving force of the model level are gradually enhanced from the surface layer to the deep layer, and the dependence is gradually weakened.**

***Keywords*—digital education resources, precise recommendation, Interpretive Structural Modeling (ISM), Matrices Impacts Croises-Multiplication Appliance Classement (MICMAC)**

I. INTRODUCTION

Internet technology has accelerated the transformation of information resources from “scarce” to “rich” era, and caused the problem of “information overload” [1]. Meanwhile, with the continuous and in-depth advancement of education informatization, various digital education resources are also growing exponentially [2]. Facing abundant digital resources, learners also need to put more time and energy to obtain personalized high-quality resources that are suitable for their learning. In particular, in many cases, learners’ resource needs are uncertain or difficult to accurately express, which requires a new resource filtering mechanism to help them predict and recommend high-quality resources of interest in a large number of digital resources without a clear search purpose. Recommendation technology has become an effective means to solve the contradiction between the infinite abundance of information resources and people’s limited attention. This has also become a hot spot of applied research in the field of personalized service of digital educational resources. The purpose of the digital resource recommendation service is to use appropriate recommendation algorithms to recommend appropriate learning resources from a large number of learning resources according to the learner’s preference, style, cognitive level and other element models, thereby reducing the learner’s resource search cost. So that learners with different usage preferences and cognitive levels can easily obtain high-quality resources and service that meet their personal development needs [3].

Learners are the core of digital educational resource recommendation services, and a comprehensive and accurate representation of their interests, preferences, cognitive styles, behavioral motivations and other characteristics is the premise of personalized recommendation [4]. However, learner models have a complex form of representation with both dynamic attribute elements and dynamic generative content [5]. It plays a key role in the effectiveness of digital educational resource recommendation services to clarify the influence relationship between various elements of learners’ characteristics, accurately describe the overall profile of learners and their dynamic behaviors [6]. In-depth analysis of the influence degree of user characteristics factors is conducive to optimizing the user model and improving the accuracy of resource recommendation, so as to meet the requirements of the national new education infrastructure construction plan and the demand for adaptive learning services. In-depth analysis of the influence of user characteristic factors on the accurate recommendation of digital educational resources and the relationship between these factors, which is beneficial to optimizing the user model, improving the accuracy of resource recommendation, and meeting the requirements of the national education new infrastructure construction plan and the needs of adaptive learning services [7]. The major content of this paper includes the following:

1) On the basis of the relevant research results of the user model of the recommendation system, the candidate set of user-related characteristic factors affecting the recommendation of digital resources is summarized through literature analysis;
2) Delphi method is used to obtain the user characteristic analysis framework and dimension indicators that affect the recommendation of digital education resources;
3) Based on the ISM model method, the internal relationship between each user characteristic factor is clarified, and the element hierarchical structure relationship diagram is obtained;
4) The MICMAC analysis method is used to calculate the driving force and dependence of each influencing element. The influence process of each user characteristic element on the resource recommendation effect is further clarified;

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5) Finally, based on the research results, the enlightenment of user modeling for accurate recommendation of digital educational resources is proposed, which provides a reference for the realization of personalized resource recommendation services.

II. Research Methods

A. Delphi

Delphi is a research method that draws on the expertise and experience of experts through expert questionnaires, which is complemented by controlled feedback from perspectives to make intuitive predictions, and it is also the process of obtaining the maximum consensus of the group of experts [8]. In general, the Delphi method requires two or more rounds in order to allow respondents to participate more in the study and to propose a gradual revision of the expert consultation form based on scoring and opinions, and finally to reach an agreed opinion [9]. In the process of scoring the importance of each characteristic factor, the Rickett five-point scoring method is used, and the scoring range is 1-5 points, for example: 1 point means very unimportant, and 5 points means very important.

B. ISM

ISM is used as an analytical tool to establishes and selects the elements constituting the system as comprehensively as possible through discussions and empirical analysis of some disordered, discrete, and static systems, and constructs an adjacency matrix and a reachability matrix according to the detailed list of elements. After decomposing the reachability matrix, the purpose of establishing the structural model is achieved, and the structural model is explained [10]. This method is used to sort out and analyze the user characteristic factors, and the two-dimensional matrix operation is used to obtain the correlation between all factors in the system, and the hierarchical relationship between the factors affecting the user's resource selection features is formed.

C. MICMAC

MICMAC method is used to analyze the role of relationship among system factors. It mainly classifies the factors by analyzing the relationship between the factors, and estimate the driving force of the factors according to the hierarchical circular arrival path of each relationship and dependency, then clarify the status and role of each influencing factor in the system [11]. The MICMAC is a method of classifying elements in a system using cross-influence matrix multiplication, and it is generally used to analyze the importance of elements in a system in a complex environment and match the corresponding solutions to problems [12]. According to the two values of the driving force and dependence of the elements, the cross-influence matrix multiplication classification method divides the factors into four categories: independent factors, connection factors, autonomous factors and dependent factors. Independent factors refer to factors with strong driving force but weak dependence, which do not depend on other factors and are usually the most critical factors in the system. The linkage factor refers to the factor that is very strong in driving force and dependence, and any change in behavior related to these factors will have an impact on other factors, and in turn have an impact on itself, so these factors are very unstable. The dependence and driving force of autonomous factors are weak, while dependent factors have higher dependencies and weaker drivers.

III. Research Process and Results

A. Data Sources

Firstly, to analyze the real influencing factors, we screened the user characteristic factors that have influenced the recommendation of digital education resources over the past 10 years and extracted core elements from the expert consultation table. The expert consultation form was distributed to 30 pre-screened authoritative experts, who rated the importance of each element and suggested revisions. Secondly, the study was conducted two rounds of expert opinion consultation. A total of 30 expert consultation questionnaires were issued, and 30 valid questionnaires were recovered, with a recovery rate of 100%. According to the results of the first round of feedback, 90% of the experts expressed their approval of the index system design.

The experts' opinions are mainly concentrated in the following five points: the explanation of the cognitive level is inaccurate; replacing "cognition and skills" with "cognitive characteristics" in the first-level indicator; merge "cognitive ability" with "cognitive level"; delete "learning methods" under the preference characteristics; and add the second-level indicator of "resource requirements". The study reinterpreted the cognitive levels in the second round of questionnaires based on the feedback collected in the first round. The first-level index "cognition and skills" is replaced by "cognitive characteristics"; Combine "cognitive ability" and "cognitive level" into "cognitive level"; delete the secondary index "learning style"; and add the secondary index under the preference characteristic dimension. According to the analysis of the results of the second round of expert consultation, the experts did not delete their opinions and the scores and suggestions of each feature were roughly consistent, so the expert consultation was stopped.

Finally, according to the scores of each characteristic factor, the average score was arranged in the order from the highest to the bottom, and the results were as follows: learning motivation, information literacy, social attributes, resource feature preference, resource demand, interactive preference, learning emotion, learning attitude, learning style, individual attributes, learning engagement, cognitive level, cognitive structure. As shown in Table 1, all characteristic factors are sorted in order of importance and coded as Z1, Z2, Z3...... Z13.

Table 1. User characteristic factors influencing the recommendation of digital educational resources

classification	Influential factors	Code	describe
Natural characteristics	Individual attribute	Z10	The identity of the user is the basic characteristic that distinguishes it from other users, such as: name, gender, and age.
	Social attribute	Z3	The user's personal social network and external personal circumstances, such as professional, academic background and professional background.

Dynamic characteristics	Motivation to learn	Z1	It mainly includes the measurement of interest, perceived ability and effort, including cognitive drive, self-improvement drive and affiliated drive.
	Learning emotions	Z7	Refers to the attitude towards educational resources arising with the process of user cognition and consciousness, the stronger the enthusiasm of learning behavior, the stronger the emotional.
	Learning attitude	Z8	Learn the more lasting positive or negative behavior tendency or internal reaction readiness.
	Learning engagement	Z11	Characterize the user's initiative and effort to participate in the use of resources.
Cognitive characteristics	Information literacy	Z2	The ability to acquire, process, handle and transfer resources.
	Cognitive level	Z12	It characterizes the degree of mastery of knowledge of knowledge, and generally adopts knowledge, understanding, application, analysis, comprehensive, and evaluation.
	Cognitive structure	Z13	Refers to the entire content of the user's existing ideas and their organization.
Preference characteristics	Resource characteristic preferences	Z4	When selecting the user to choose the resource, it indicates the preferences of the resource presentation, such as text, picture sound, video.
	Resource requirements	Z5	It is the most direct resource demand of users, and can more intuitively express user's demand for resource content and type.
	Interaction preferences	Z6	It is mainly divided into interaction between users and users, user's and resource interactions.
	Learning style	Z9	To characterize the differences in the user's individual characteristics and thinking styles, it is divided into: Perception-intuitive type, visual type - speech type, Active-reflection type, serial type - global type.

B. Adjacency Matrix

The adjacency matrix can clearly show the direct relationship between each user characteristic factor. According to the steps of the interpretive structural model method, before establishing the link matrix, it is necessary to clarify the internal relationship between the user characteristic factors. In this study, the binary relationship diagram is used to represent the logical relationship among the influencing factors, and all the binary ordered arrangement are used to draw up a multi-level matrix. Furthermore, the adjacency matrix **M** is used to represent the relationship among the 13 factors, and the relationship between the factors is represented by 0 and 1 respectively (1 indicates that the row has a direct impact on the column, and 0 indicates that the row has no direct impact on the column).

The relationship between the factors exists in the ways following situations: Zi~Zj, Zi and Zj have an interrelationship to form a loop; $Zi \times Zj$, Zi and Zj are not related to each other; $Zi>Zj$, Zi is related to Zj, Zj is not related to Zi; $Zi<Zj$, i.e., there is no relationship between Zi and Zj, while there is a relationship between Zj and Zi. The so-called adjacency matrix defines the relationship between Zi and Zj [13, 14]. The values between the factors in the matrix are defined as follows:

$$Zij=\begin{cases} 0 \text{ Factor i has a direct impact on factor j} \\ \qquad\qquad (i, j=1, 2, 3, 4, \ldots\ldots, 14, 15) \\ 1 \text{ Factor i has no direct effect on factor j} \end{cases}$$

The sorting out of the direct relationship between user characteristic factors establishes the adjacency matrix. According to the above formula, the direct relationship between user characteristic factors is obtained to establish the adjacency matrix. To facilitate the calculation of the adjacency matrix, only the direct influence relationship is considered when there is an intersection between the feature factors. The adjacency matrix is shown in Table 2.

Table 2. Adjacency matrix **Z** of user characteristic factors affecting the recommendation of digital education resources

	Z1	Z2	Z3	Z4	Z5	Z6	Z7	Z8	Z9	Z10	Z11	Z12	Z13
Z1	0	0	0	0	0	0	1	1	0	0	1	0	0
Z2	0	0	1	0	0	0	0	0	0	0	0	1	1
Z3	0	0	0	0	0	0	1	1	0	0	1	0	0
Z4	0	0	0	0	1	0	0	0	0	0	0	0	1
Z5	0	0	1	1	0	1	0	0	0	0	1	1	1
Z6	0	0	1	0	1	0	0	1	0	0	0	0	0
Z7	0	0	0	0	1	1	0	1	0	0	0	0	0
Z8	1	0	0	0	1	1	0	0	0	0	1	0	0
Z9	0	0	1	1	1	1	0	0	0	1	1	0	0
Z10	0	0	1	0	0	1	0	0	0	0	0	0	0
Z11	0	0	1	0	1	0	1	0	0	0	0	0	0
Z12	0	1	0	0	1	0	0	0	0	0	1	0	1
Z13	0	0	1	0	1	0	0	0	0	0	0	1	0

C. Establish a Reachability Matrix

The above adjacency matrix presents the direct relationship between the various user characteristic factors. In addition to, the direct relationship in the adjacency matrix is also an indirect relationship. The reachability matrix presents the indirect relationship of each characteristic factor [7]. The reachable matrix R represents the indirect relationship between nodes in the form of a matrix, and is transportable [8]. The calculation of the reachable matrix is based on the adjacency matrix. Firstly, the sum of Z' and the identity matrix I is $Z+I$. Secondly, the power operation of the matrix $Z+I$ is done. Finally, the power calculation is carried out through the Boolean operation until $(Z+I)\ k\text{-}1 \neq (Z+I)\ k$

$= (Z+I)\ k+1 = R$, and the reachable matrix is obtained. In the reachable matrix operation, 0+0=0, 0+1=1, 1+0=1, 1+1=1, 0×0=0, 0×1=0, 1×1=1.

The study model involves 13 variables, and the calculation process is relatively lengthy. To improve the accuracy of the calculation, we use python to calculate the above adjacency matrix to obtain the reachability matrix R (shown in Table 2). It can be obtained by calculation: when K=4, $Z'=(Z+I)k$-1=$(Z+I)k \neq (Z+I)k$+1, satisfying the conditions of Boolean operations, notation up to the matrix Z'=(Z+I). Finally, the matrix R is arranged in ascending order by rows, while the corresponding column elements are reordered and stratified to obtain the reachability matrix, as shown in Table 3.

Table 3. The user characteristic factors that affect the recommendation of digital education resources can reach Matrix **R**

	Z1	Z2	Z3	Z4	Z5	Z6	Z7	Z8	Z9	Z10	Z11	Z12	Z13
Z1	1	0	1	0	1	1	1	1	0	0	1	0	0
Z2	1	1	1	0	1	1	1	1	0	0	1	1	1
Z3	1	0	1	0	1	1	1	1	0	0	1	0	0
Z4	1	1	1	1	1	1	1	1	0	0	1	1	1
Z5	0	0	0	0	1	0	0	0	0	0	0	0	0
Z6	1	0	1	0	1	1	1	1	0	0	1	0	0
Z7	1	0	1	0	1	1	1	1	0	0	1	0	0
Z8	1	0	1	0	1	1	1	1	0	0	1	0	0
Z9	1	1	1	1	1	1	1	1	1	1	1	1	1
Z10	1	0	1	0	1	1	1	1	0	1	1	0	0
Z11	1	0	1	0	1	1	1	1	0	0	1	0	0
Z12	1	1	1	0	1	1	1	1	0	0	1	1	1
Z13	1	1	1	0	1	1	1	1	0	0	1	1	1

D. *Hierarchy of Influencing Factors*

After calculating the matrix, the user characteristic indicators in the matrix are divided hierarchically to make the causal relationship between the elements clearer. Table 3 shows the leading and reachable sets of each factor. R(Zi) represents the set of elements that element Zi can reach, that is, the set of all rows where the corresponding element is listed as 1. A(Zi) represents the set of elements that will reach the feature Zi, that is, the set of elements corresponding to all the rows whose matrix elements are 1 in the Zj column of the reachable matrix. According to the distribution of the reachability matrix in Fig. 1, it is transformed and divided into user feature index levels. According to R(Zi) ∩ A(Zi)=R(Zi), the factor set of each layer can be determined through python programming. The first layer user feature index element set cannot reach the set of other elements. The second layer of user characteristic index factor set needs to delete all the factor sets of the first layer, and then use the same way to determine the first layer. All the other layer user characteristic index element sets need to be carried out in this way until all the elements are calculated.

Table 4. Reachable set and antecedent set of the highest level (analysis of relationship among factors)

Element Zi	R(Zi) Reachable set	A(Zi) Antecedent set	R(Zi)∩A(Zi)
Z1	1, 3, 5–8, 11	1–4, 6–13	1, 3, 6, 7, 8
Z2	1–3, 5–8, 11–13	2, 4, 9, 12, 13	2, 12, 13
Z3	1, 3, 5–8,11	1–4, 6–13	1, 3, 6, 7, 8
Z4	1–8, 11–13	4, 9	4, 9
Z5	5	1–13	5
Z6	1, 3, 5–8, 11	1–4, 6–13	1, 3, 6, 7, 8
Z7	1, 3, 5–8, 11	1–4, 6–13	1, 3, 6, 7, 8, 11
Z8	1, 3, 5–8, 11	1–4, 6–13	1, 3, 6, 7, 8, 11
Z9	1–13	9	9
Z10	1, 3, 5–8, 10, 11	9, 10	10
Z11	1, 3, 5–8, 11	1–4, 6–13	6, 7, 8, 11
Z12	1–3, 5–8, 11–13	2, 4, 9, 12, 13	2, 12, 13
Z13	1–3, 5–8, 11–13	2, 4, 9, 12, 13	2, 12, 13

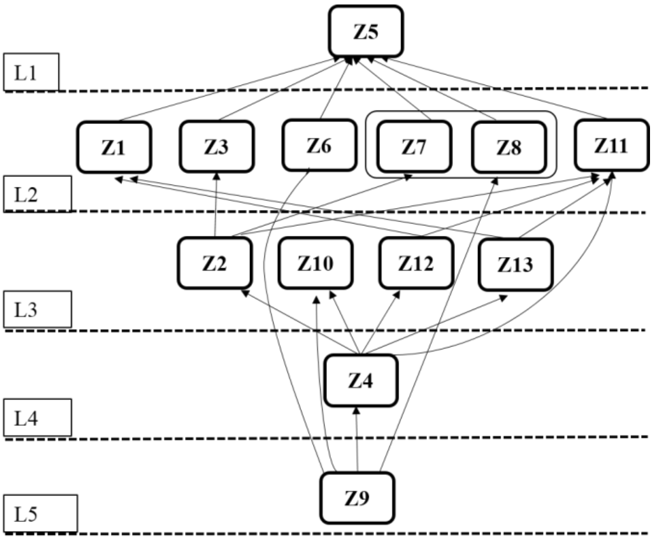

Fig. 1. User characteristics that influence digital education resource recommendations are ISM.

According to the hierarchical partitioning conditions, when the first-level reachable set and the anhedonic set satisfy the R(Zj)=R(Zj)∩A(Zi) condition, the highest factor Z5 can be determined, as shown in Table 4. The smallest factor Z9 can be determined when A(Zi)=R(Zj) ∩ A(Zi) is satisfied. Through many iterations of programming calculation, the final output of the first layer element is {Z5}; The second layer of elements is {Z1, Z3, Z6, Z7, Z8, Z11}. The third layer element is {Z2, Z10, Z12, Z13}. The fourth layer element is {Z4}. The fifth layer feature is {Z9}. According to the reachability matrix in Table 4, the hierarchical division of each user characteristic index is analyzed, and the user characteristic hierarchy affecting the recommendation of digital education resources is derived, as shown in Fig. 1. The level of the model is bottom-up, which indicates good stability and large coverage [15].

E. *MICMAC Classification*

To further analyze the degree of influence of each user characteristic factor on the recommendation of digital educational resources, MICMAC analysis method is used to calculate the driving force and dependency of each influential factor corresponding to the number of "1" rows and columns [16]. According to the driving force and dependence of various factors, the first quadrant of the entire coordinate system is divided into 4 areas, which represent independent factors, connection factors, autonomous factors, and dependent factors, as shown in Fig. 2. The results of the influencing factors are concluded according to the quadrants in the Fig. Z2, Z4, Z9, Z12, and Z11 are in independent factors. Z1, Z3, Z7, Z6, Z8, and Z10 are in contact factors. Z5 and Z13 are in the dependent factors.

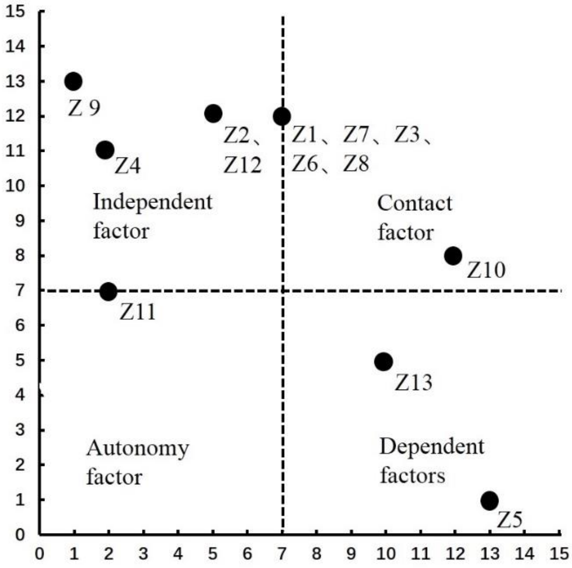

Fig. 2. User characteristic factors based on MICMAC analysis.

IV. Discussions

A. ISM Analysis

According to the research results of ISM model combined with the actual situation, the user characteristics influencing digital educational resource recommendation can be divided into 5 levels and 3 categories. Figure 1 shows that the 13 user characteristic factors are a stepless multi-level system and each factor influences the resource recommendation effect through interaction. The model divides 5 levels into 3 groups, namely top-level design factor group, key factor group and direct factor group. Among them, learning style and resource feature preference are located in the top-level design factor groups L4 and L5. From the above, learning style and resource feature preference directly or indirectly affect other factors, which is the basis and prerequisite for resource recommendation. Therefore, top-level design and clear learner preferences should be emphasized in resource recommendation. L3 and L2 belong to the key factor group, including: motivation factor and cognitive factor. Among them, information literacy, individual attribute, cognitive level and cognitive structure depend on learning style and resource characteristic preference, and then affect learning motivation, social attribute, interactive preference, learning emotion, learning attitude and learning engagement. The result indicate that the key factors are regulated, supported and influenced by the top-level design factors and act on the direct factors. L1 belongs to the direct factor group, and the direct factor include the resource demand, which is the most intuitive judgment and representative evaluation index reflecting the resources required by users.

B. MICMAC Analysis

According to Fig. 2, learning input belongs to autonomous factor cluster, which has low dependence, driving force and relatively independent. Compared with other factors, it is easier to master and should be controlled first. Resource demand and cognitive structure belong to the dependent factor cluster, showing high dependence and low driving force. Indicating that these factors are greatly affected by other factors that directly affect the accuracy of digital education resource recommendation. Learning motivation, social attribute, interactive preference, learning emotion, learning attitude and individual attribute belong to the linkage factor cluster with high dependence and high driving force. It shows that each user characteristic factor is weakly independent and highly correlated, and that any change will have an impact on other factors and feedback on itself. Information literacy, preference for resource characteristics, learning style, and cognitive level belong to independent factor clusters with low dependency and high driving force. This suggests that the influencing factors of such clusters are broader and less susceptible to the influence of other factors. If the influencing factors in this quadrant are well resolved, they will have a positive promoting effect on the solution of other factors.

V. Conclusion

There are many influencing factors and complex mechanism of the user characteristics that affect the recommendation of digital educational resources. In this paper, by analyzing and condensing the user characteristic factors affecting the recommendation of digital educational resources, the ISM technique is used to clarify the logical relationship between the 13 key characteristic factors and establish an explanatory structure hierarchy model. Then MICMAC is used to analyze the dependency and driving force of each characteristic factor in the model and determine its degree of influence. This study can more clearly recommend the characteristics of users, improve the accuracy and efficiency of recommendation, and provide reference value for the recommendation of digital educational resources. At the same time, the research results determine the key factors and priority links that affect the recommendation of digital educational resources, and provide practical suggestions for the construction of resource recommendation system. In the process of building the recommendation system, we should grasp the user’s cognitive state (source factor) in time, fully tap the user’s core characteristics, strengthen the personalized recommendation of multi-dimensional feature differences, and update the user’s resource needs in real time. Finally, the purpose of optimizing the resource recommendation sequence is achieved.

Conflict of Interest

The authors declare no conflict of interest.

Author Contribution

Qinying Zhou contributed to analysis and manuscript preparation. Xiaoyu Ma made a questionnaire. Leilei constructed model. Guojun analyzed the data. All the authors read and approved the final manuscript.

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